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Scale Meets Networks: Interactions and Multi-path Transmission Mechanisms between Urban Economic Scale and Innovation Networks in China

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Scale Meets Networks: Interactions and Multi-path Transmission Mechanisms between Urban Economic Scale and Innovation Networks in China

Abstract: Under the context of innovation driven development and highly mobile production factors, the interaction between urban economic scale and innovation networks increasingly shapes urban hierarchy restructuring and regional innovation development. Using 1,790,452 patent cooperation records among 296 Chinese cities from 2018 to 2023, this study employs a generalized structural equation model (GSEM) to examine their bidirectional interaction and mediation mechanisms. The results show that urban innovation linkages and economic scale exhibit a converging superlinear relationship. Urban economic scale and innovation networks form a positive feedback cycle, with economic scale exerting a stronger effect on networks than the reverse effect. Labor matching positively mediates the effect of economic scale on innovation networks, whereas industrial agglomeration produces a negative lock in effect and policy pathways show contextual dependence. In the reverse direction, industrial upgrading serves as an effective pathway within city categories, while local innovation transformation remains unstable and population agglomeration exhibits heterogeneous effects across scales and city types. These findings provide implications for optimizing urban innovation networks and promoting coordinated urban development.

Keywords: Urban economic scale; Innovation networks; Interaction mechanism; Transmission pathways; Generalized Structural equation modeling

1. Introduction

Under the context of innovation driven development and highly mobile production factors, the spatial organization of urban systems is undergoing profound restructuring (Coe and Yeung, 2015). On the one hand, the long-established size-based hierarchical structure of urban systems has shaped the fundamental patterns of factor agglomeration and resource allocation, exerting top-down influences on the spatial distribution of knowledge spillovers and innovation activities (Fujita and Thisse, 2002; Zheng et al., 2023; Fan et al., 2021). On the other hand, with the increasing importance of knowledge spillovers, technological collaboration, and industrial linkages, urban development depends not only on internal attributes but also on a city's position and connections within broader networks (Taylor, 2007; Castells, 1996). Innovation activities have become deeply embedded in

inter-city and cross-regional network structures, and multi-scalar innovation collaboration networks are reshaping urban functional divisions and development opportunities (Fotopoulos, 2023; Wang et al., 2025).

Currently, China's regional development strategies emphasize the cultivation of regional central cities to stimulate surrounding areas. Yet, this process is often accompanied by a "strong core–weak periphery" pattern in practice (Du et al., 2024; Zhou et al., 2026b). A limited number of megacities concentrate most high-end innovation resources and network hub functions and become core nodes within the national innovation network. In contrast, many small and medium-sized cities remain peripheral or dependent within innovation networks because of their limited scale and weak resource attraction capacity (Xian et al., 2018; Gui et al., 2021). As shown in Figure 1, the patent cooperation network in China from 2018 to 2023 exhibits a hierarchical pattern characterized by an absolute core centered on Beijing, with Shanghai, Shenzhen, Guangzhou, Nanjing, Hangzhou, and Chengdu serving as major nodes, together with an east dense and west sparse spatial structure. This observation raises several critical questions: Does a scale based urban hierarchy strengthen or weaken a city's position within innovation networks? Does the expansion and evolution of innovation networks generate synergistic effects, or does it reinforce existing hierarchical inequalities? What mechanisms and pathways govern the interaction between these two dimensions? Addressing these questions is essential for optimizing the spatial organization of China's urban innovation networks and promoting coordinated development between urban scale and innovation capacity.

Figure 1 Spatial distribution of China's innovation network based on patent cooperation (2018, 2023)

Theoretically, research on the spatial organization of urban systems has evolved along two major strands, namely the "central place" and the "space of flows" perspectives. The hierarchical spatial paradigm rooted in central place theory emphasizes vertical and hierarchical spatial logic and highlights the role of urban scale in factor agglomeration, knowledge spillovers, and innovation efficiency (Shearmur and Doloreux, 2015; Wang et al., 2021; Shijun et al., 2010). In contrast, the network paradigm based on the theory of the space of flows focuses on the flows of knowledge, information, talent, and capital across cities, highlighting that urban development depends on cross-scalar factor flows and network linkages (Camagni and Capello, 2004; Castells, 1996). This perspective argues that urban competitiveness increasingly depends on the degree and manner of

network embeddedness rather than solely on scale attributes (Meijers, 2007). Nevertheless, growing evidence suggests that hierarchical and network-based spatial patterns are not mutually exclusive but rather co-exist in complex, intertwined relationships (Derudder and Taylor, 2018; Zheng et al., 2024). On this basis, some studies identify spatial structures in which regional hierarchies and network linkages overlap and interact (Hao et al., 2023; Xi et al., 2025). Zhou et al. (2026a) further argue that urban regional evolution results from interactions between hierarchical space and flow space, and they reveal a positive interaction between population flows and urban scale hierarchy.

Although existing studies provide important insights into the relationship between urban scale and innovation networks, two key limitations remain. First, current studies mainly focus on one directional causal relationships by either emphasizing the determining role of urban scale in network position (Bokányi et al., 2022; Bettencourt et al., 2007) or examining the contribution of network centrality to urban growth and innovation performance (Wang et al., 2025; Zhou et al., 2024), while lacking a systematic examination of their bidirectional interaction mechanisms. Second, the multidimensional transmission pathways between urban hierarchy and innovation networks have not been thoroughly decomposed, and the mechanisms and heterogeneous effects of different pathways remain insufficiently identified and empirically tested.

In response, this study focuses on disentangling the multidimensional interaction pathways between urban economic scale and innovation networks and systematically examines their bidirectional mechanisms and heterogeneous characteristics. The research framework is organized as follows. Section 2 presents the theoretical framework, constructing an analytical model of urban hierarchy–network interactions from a coupling perspective. Section 3 introduces the methodology, including the identification of the power-law relationship through urban scaling laws and the construction of a structural equation model. Section 4 presents the empirical results, systematically examining the bidirectional mechanisms and their pathway decomposition. The final section concludes and discusses policy implications.

2. Theoretical Framework

The relationship between urban economic scale and innovation networks does not operate through a single mechanism. Instead, it takes the form of a complex structure in which direct interactions coexist with multiple indirect transmission pathways (Figure 2). The influence of urban economic scale on innovation networks is not only reflected in its direct effect of enhancing network centrality

and control through scale advantages, but also in its indirect reinforcement or inhibition of network embeddedness through channels such as agglomeration economies, labor matching, and policy preferences. Similarly, the feedback effect of innovation networks on urban hierarchy is not limited to the direct promotion of urban scale through network centrality, but also operates through mechanisms such as innovation attraction, local research and development, and industrial relocation, which continuously reshape urban economic scale.

Figure 2 Theoretical analysis framework

From the perspective of urban economic scale affecting innovation networks, urban scale enhances its attractiveness and control within innovation networks through comprehensive advantages such as market potential, information accessibility, and institutional environment. As a result, higher level cities are more likely to emerge as core nodes in innovation networks (Yao and Wu, 2022; Zheng et al., 2024; Zhang et al., 2026). At the indirect level, the impact of urban hierarchy on innovation networks can be decomposed into three main pathways.

First, the agglomeration economy pathway. Cities with higher economic scale typically exhibit stronger capacity for firm agglomeration, which facilitates cross boundary interactions among innovation actors and strengthens intercity innovation linkages (Hu et al., 2025a; Chen et al., 2022). However, excessive agglomeration may also induce path dependence and resource exclusivity, thereby inhibiting the spatial expansion of innovation networks (Boschma, 2005).

Second, the labor matching pathway. Higher level cities are generally more capable of attracting interregional flows of high skilled labor and innovation talent (Qin et al., 2026; Davis and Dingel, 2020). Daily population mobility not only enhances cities' absorptive capacity of knowledge but also improves labor market matching efficiency, thereby increasing the likelihood of inter-city innovation collaboration (Bonaventura et al., 2021; Schmutz-Bloch and Sidibé, 2024).

Third, the policy bias pathway. In the Chinese context, higher level cities are more likely to obtain centralized and local governmental support for science and technology resource allocation, forming a pronounced policy preference effect (Liu et al., 2024). This policy advantage strengthens a city's organizational and controlling role within regional innovation networks by increasing R&D investment. However, such preferential allocation may also reinforce a ``strong center'' structure, leading to a club effect in which innovation resources concentrate in a limited number of core cities (Cui and Tang, 2023).

On this basis, the following hypotheses are proposed:

Hypothesis 1: Urban economic scale promotes intercity innovation linkages, thereby enhancing a city's centrality in innovation networks.

Hypothesis 2: Urban economic scale enhances intercity innovation linkages through industrial agglomeration.

Hypothesis 3: Higher level cities improve labor market matching efficiency through intercity population mobility, thereby strengthening their embeddedness in innovation networks.

Hypothesis 4: Higher level cities increase their network centrality through policy bias in favor of innovation.

From the perspective of the feedback effects of innovation networks on urban hierarchy, a city's centrality within innovation networks itself constitutes a critical development resource. By improving information accessibility, facilitating knowledge exchange, and strengthening external linkages, it directly promotes urban economic expansion and functional upgrading (Zhou et al., 2026a; Wang et al., 2025). At the indirect level, innovation networks also influence urban hierarchy evolution through three pathways.

First, the factor agglomeration pathway. Higher centrality in innovation networks implies greater innovation vitality, which enhances the city's attractiveness to population, capital, and technology, thereby promoting economic scale expansion (Li and Neal, 2024). However, due to agglomeration shadows, strengthened network linkages may also lead to population outflows in some cities, thereby weakening urban economic hierarchy (Zhou et al., 2023).

Second, the local innovation pathway. Innovation networks improve knowledge accessibility, facilitate technological diffusion, and promote collaborative R&D, thereby directly enhancing urban innovation output and strengthening economic growth momentum (Fan et al., 2025; Wang et al., 2025; Cantwell and Zaman, 2024).

Third, the industrial relocation and structural upgrading pathway. Innovation networks accelerate industrial upgrading by facilitating technology diffusion and embedding high end producer services, thereby promoting urban economic scale expansion (Sun et al., 2026). However, network preferential attachment and club effects may concentrate upgrading gains in core nodes, thereby deepening disparities in urban economic scale (Hu et al., 2025b).

Accordingly, the following hypotheses are proposed:

Hypothesis 5: Innovation networks, as a development resource, directly promote urban economic scale growth.

Hypothesis 6: Innovation network embeddedness enhances urban economic growth by population agglomeration.

Hypothesis 7: Innovation network embeddedness promotes urban economic growth through enhanced local innovation capacity.

Hypothesis 8: Innovation network embeddedness promotes urban economic growth through industrial structure upgrading.

3. Methodology

3.1 Data

Considering data availability and completeness, and excluding cities with substantial missing values, the final sample comprises 296 prefecture-level and above cities (excluding Hong Kong, Macao, Taiwan, and cities with serious lack of socioeconomic data) for the period 2018–2023. The socio-economic data are obtained from the China Urban Statistical Yearbook from 2019 to 2024, and missing values are supplemented using Statistical Bulletin of National Economic (2018–2023) issued by the China National Bureau of Statistics (http://www.stats.gov.cn/tjsj).

The urban innovation network is constructed using joint invention patent applications disclosed by the China National Intellectual Property Administration (CNIPA, https://pss-system.cponline.cnipa.gov.cn/conventionalSearch). Specifically, all invention patents jointly applied for by two or more institutional applicants during 2018–2023 are extracted, and patents whose applicants are exclusively individuals or individual–institution combinations are removed, yielding a final dataset of 1,790,452 collaborative invention patents.

Data on population flows are derived from Gaode (Amap) intercity migration big data, using the city-to-city migration scale index for June of each year from 2018 to 2023. This period is selected to minimize distortions from major holidays and to avoid significant disruptions caused by the pandemic, as June represents a relatively stable timeframe nationwide.

3.2 Identification of the Relationship Between Urban Economic Scale and Innovation Networks

(1) Identification of the power-law relationship

According to the Urban Scaling Law, socio economic attributes of cities typically scale nonlinearly with city size (Bettencourt et al., 2007). Empirical evidence from Jiang et al. (2025) further verified

that intercity enterprise investment and GDP followed a power law pattern. Therefore, this study extends the urban scaling framework to the domain of innovation networks and examines the power law relationship between urban economic scale and innovation network centrality as follows:

$$NC_i = \alpha GDP_i^{\beta} \tag{1}$$

where *GDP* represents the gross domestic product of city *i*, capturing its economic scale, and *NC* denotes the total number of patent collaboration links between city *i* and all other cities in the patent cooperation network, representing its innovation network centrality. α is a scaling constant and β is the scaling exponent. When $\beta = 1$, innovation network centrality scales linearly with economic size; when $\beta > 1$, a superlinear relationship exists; and when $\beta < 1$, a sublinear relationship is observed.

Taking logarithms on both sides of Equation (1) yields:

$$lnNC_i = \alpha + \beta lnGDP_i + \varepsilon \tag{2}$$

The residual for each city is computed as:

$$\varepsilon = lnNC_i - (\alpha + \beta lnGDP_i) = ln\frac{NC_i}{\alpha GDP_i^{\beta}} \tag{3}$$

The residual ε captures the deviation of a city's innovation network centrality from the level predicted by its economic scale. A positive value indicates that the city's embeddedness in the innovation network exceeds its expected level given its economic size, while a negative value indicates a lagging position.

(2) City classification

Based on the residual analysis above and comparing city economic scale with the national median in each year (M_GDP), this study classifies cities into four categories: network driven cities, leapfrogging cities, resource mismatch cities and double lagging cities (Table 1).

3.3 Generalized Structural Equation Modeling

The Generalized Structural Equation Modeling (GSEM) allows for the estimation of bidirectional causal relationships among variables and decomposes total effects into direct and indirect effects. Therefore, this framework is suitable for simultaneously identifying the two-way relationship between economic scale and innovation networks and the associated mediation pathways.

Building on the theoretical framework, urban economic scale (ln*GDP*) and innovation network centrality (ln*NC*) are specified as the core variables. The former is proxied by gross domestic product,

while the latter is measured by total number of patent collaborations. In the pathways from urban economic scale to innovation networks, three mediating mechanisms are specified. The industrial agglomeration is proxied by the number of above-scale industrial enterprises (ln*indus*), which effectively captures how agglomeration economies reinforce cities' hub positions in innovation networks (Frenken et al., 2007). The labor matching pathway is represented by an index of inter-city population flows (ln*flow*), reflecting the depth of the local labor pool and matching efficiency (Schmutz-Bloch and Sidibé, 2024), and capturing how factor allocation efficiency enhances network connectivity. The policy preference pathway is proxied by science and technology expenditure (ln*tech*), capturing the role of government resource allocation and institutional support in shaping a city's position in innovation networks (Hu and Xue, 2021).

Regarding the pathways through which innovation networks influence urban economic scale, three mechanisms are also specified. The population agglomeration pathway is proxied by urban resident population (ln*pop*), capturing the role of innovation networks in promoting economic growth through population concentration. The local innovation pathway is measured by the number of granted patents (ln*innov*), reflecting how network embeddedness enhances knowledge diffusion and R&D output, thereby driving economic growth (Caragliu and Del Bo, 2019; Xie et al., 2024). The industrial structure upgrading pathway is measured by an industrial structure index (*upon*), and this index is calculated as $\sum_{i=1}^{n} \theta_i \times q_i$, where θ_i denotes the weight assigned to each sector**,** q_i represents the share of output of each sector using the weighted summation method (Li, 2020)).

To control for temporal trends, year dummy variables are included in all equations. Following the principles of GSEM specification, a structural equation model is constructed to capture both the direct interactions and multidimensional transmission pathways between urban hierarchy and innovation networks (Figure 3).

Figure 3 Structural equation model of the interaction between urban hierarchy and innovation networks

The model is estimated using the gsem command in Stata 17 with maximum likelihood (ML). To account for within city serial correlation across years, clustered robust standard errors are used at the city level with city id as the clustering variable. To reduce heteroscedasticity, all variables except the industrial structure index are log transformed. Descriptive statistics for all variables are reported in Table 2.

Table 1 City classification based on economic scale and superlinear deviation

Type	Economic scale	Innovation performance	Description
Network driven cities	GDP>M_GDP	$\varepsilon>0$	Large economic scale and strong innovation network performance, forming a virtuous cycle
Leapfrogging cities	GDP≤M_GDP	$\varepsilon>0$	Small economic scale but active innovation networks, with potential for leapfrog development
Resource mismatch cities	GDP>M_GDP	$\varepsilon<0$	Large economic scale but relative lagging innovation networks, indicating structural contradictions
Double lagging cities	GDP≤M_GDP	$\varepsilon<0$	Both economic scale and innovation networks lag behind, placing the city in a marginalized position

Table 2 Descriptive statistics of variables

Variable	Indicator	Mean	Std. Dev.	Min	Max
Economic scale (ln*GDP*)	Regional Gross Domestic Product	16.843	0.989	14.121	19.973
Policy bias (ln*tech*)	Science and Technology Input	10.756	1.596	6.662	15.529
Population flows (ln*flow*)	Population Mobility Scale Index	5.560	1.087	1.995	8.977
Industrial agglomeration (ln*indus*)	Number of above-scale industrial enterprises	6.572	1.250	1.099	9.574
Innovation network (ln*NC*)	Number of inter-city patent collaborations	5.435	1.600	0.000	11.043
Local innovation (ln*innov*)	Number of granted patents	8.046	1.682	0.693	12.540
Industrial structure	Industrial structure	2.365	0.128	1.900	2.846

Variable	Indicator	Mean	Std. Dev.	Min	Max
(*upon*)	upgrading index				
Population agglomeration (ln*pop*)	Resident population	5.815	0.784	3.148	8.075

4. Results Analysis

4.1 Characteristics and Spatial Pattern of the Relationship Between Urban Economic Scale and Innovation Networks

As shown in Figure 4, the power law exponent β between urban economic scale and innovation network centrality remains consistently greater than 1 from 2018 to 2023, indicating a pronounced superlinear relationship. This suggests that the expansion of urban economic scale drives innovation network development at an even faster rate, implying a clear scale amplification effect. The coefficient of determination (R^2) ranges from 0.737 to 0.764 across all years, indicating good model fit and gradually improving explanatory power, which further confirms the stability of the relationship between urban economic scale and innovation networks. In terms of temporal dynamics, the value of β decreases gradually from 1.479 in 2018 to 1.338 in 2023. This indicates a weakening trend in superlinear amplification, suggesting that the co-evolution between urban economic scale and innovation networks is gradually converging toward a more balanced state.

Figure 4 Power-law relationship between urban innovation network centrality and economic scale

From a spatial perspective (Figure 5), the four city types exhibit a clear hierarchical gradient structure. Network driven cities are primarily concentrated in the Yangtze River Delta, the Pearl River Delta, and the Beijing Tianjin Hebei urban agglomeration, forming the core hubs of the national innovation network. Resource mismatch cities are mostly located adjacent to network driven cities, mainly in eastern coastal and central regions, indicating that although these cities have relatively large economic scales, their innovation network embeddedness lags behind. Leapfrogging cities are mainly distributed in the periphery of the Pearl River Delta, Gansu Province, and Ningxia Autonomous Region, showing a peripheral breakthrough pattern. Double lagging cities are widely distributed in western and northeastern China, forming a marginal structure characterized by weak economic development and weak innovation capacity.

Over time, most cities remain in stable categories, accounting for 67.91%, indicating strong path dependence in the co-evolution of innovation and economic development. A total of 19.59% of cities experience upward mobility in innovation relative to their economic level, mainly transitioning from resource mismatch cities to network driven cities or from double lagging cities to leapfrogging cities. In contrast, 12.50% of cities experience a decline in innovation performance or increasing innovation lag, suggesting emerging risks of innovation network detachment. Overall, urban innovation networks and economic scale exhibit not only a significant superlinear relationship but also strong spatial heterogeneity and path dependence.

Figure 5 Spatial distribution pattern of different city types (2018, 2023)

4.2 Direct Effects of Urban Economic Scale and Innovation Networks

Figure 6 and Table 3 report the estimation results of the GSEM. From the perspective of the core bidirectional relationship, the direct effect of urban economic scale on innovation network centrality is significantly positive (0.405, $p<0.01$). This result supports Hypothesis 1, indicating that urban economic scale promotes intercity innovation linkages and thereby enhances network centrality. Cities with larger economic scale typically possess more developed innovation infrastructure and higher densities of R&D institutions. These endowments translate into greater attractiveness and control within innovation networks, enabling cities to connect more effectively with external innovation resources and to coordinate cross regional technological collaboration.

Figure 6 Estimated results of the structural equation model

At the same time, the effect of innovation network centrality on urban economic scale is also significantly positive at the 1% level (0.226, $p<0.001$). This result confirms Hypothesis 5, suggesting that innovation networks, as a key development resource, directly promote urban economic growth. This bidirectional relationship indicates a reinforcing feedback loop between scale and network, consistent with a Matthew effect in spatial economic organization, leading to increasing polarization within the urban system. Moreover, the comparison of coefficients shows that the effect of economic scale on innovation networks is stronger than the reverse effect, highlighting the dominant role of economic scale in shaping innovation network structure.

Regarding the effects on mediating variables, urban economic scale has significantly positive effects on policy preference, labor matching, and industrial agglomeration. This implies that larger cities are more likely to receive policy support, attract and match labor inflows, and develop stronger

industrial concentration. Meanwhile, innovation network centrality also has significantly positive effects on local innovation, industrial upgrading, and population agglomeration, indicating that cities located at the core of innovation networks tend to achieve higher innovation output, industrial upgrading, and population concentration.

Table 3 Estimated direct effects from the structural equation model

Pathways	Coefficient	Std. Err.	z-value	p-value
Core Bidirectional Relationship				
ln*GDP* → ln*NC*	0.405***	0.134	3.03	0.002
ln*NC* → ln*GDP*	0.226***	0.041	5.55	<0.001
Economic Scale → Mediator Variables				
ln*GDP* → ln*indus*	1.478***	0.003	463.55	<0.001
ln*GDP* → ln*flow*	0.545***	0.003	198.99	<0.001
ln*GDP* → ln*tech*	1.350***	0.144	9.35	<0.001
Mediator Variables → Innovation Network				
ln*indus* → ln*NC*	-2.270***	0.288	-7.88	<0.001
ln*flow* → ln*NC*	2.516**	1.188	2.12	0.034
ln*tech* → ln*NC*	0.171	0.487	0.35	0.726
Innovation Network → Mediator Variables				
ln*NC* → ln*pop*	0.404***	0.137	2.96	0.003
ln*NC* → ln*innov*	0.920***	0.242	3.79	<0.001
ln*NC* → *upon*	0.049***	0.018	2.73	0.006
Mediator Variables → Economic Scale				
ln*pop* → ln*GDP*	0.577***	0.125	4.61	<0.001
ln*innov* → ln*GDP*	0.143***	0.054	2.66	0.008
upon→ ln*GDP*	0.234	0.430	0.54	0.586

Note: *** p<0.01， ** p<0.05， p<0.1*

4.2 Decomposition of Indirect Transmission Pathways

Table 4 reports the results of mediation effect decomposition. The industrial agglomeration pathway shows a significantly negative mediating effect (-3.356, p<0.01), which is contrary to Hypothesis 2.

This finding suggests that excessive industrial agglomeration may generate a locking-in effect on the formation of innovation networks. Over concentration of industries leads to structural homogeneity, and firms tend to internalize R&D activities rather than engage in open collaboration, thereby reducing network openness. The labor matching pathway exhibits a significantly positive mediating effect (1.371, p<0.05), supporting Hypothesis 3. This indicates that higher level cities improve labor market matching efficiency through intercity population flows, thereby strengthening innovation network embeddedness. Cities with larger economic scale are more capable of attracting young and skilled labor, facilitating cross regional knowledge spillovers and network formation. The policy preference pathway is not statistically significant, indicating that Hypothesis 4 is not supported at the national level. This suggests that reliance on top down policy resource allocation alone is insufficient to translate into stronger positions within innovation networks.

Table 4 Estimated mediation effects from the generalized structural equation model

Pathways	Coefficient	Std. Err.	z-value	p-value
Pathways (lnGDP → lnNC)				
Via Industrial Agglomeration (ln*GDP* → ln*indus* → ln*NC*)	-3.356***	0.427	-7.86	<0.001
Via Labor Matching (ln*GDP* → ln*flow* → ln*NC*)	1.371**	0.648	2.12	0.034
Via Policy Support (ln*GDP* → ln*tech* → ln*NC*)	0.231	0.658	0.35	0.726
Pathways （ln*NC*→ln*GDP*）				
Via Population Agglomeration (ln*NC* → ln*pop* → ln*GDP*)	0.233***	0.079	2.95	0.003
Via Local Innovation (ln*NC* → lninnov → ln*GDP*)	0.132***	0.050	2.62	0.009
Via Upgrading of Industrial Structure (ln*NC* → *upon* → ln*GDP*)	0.011	0.021	0.54	0.591

Note: *** p<0.01， ** p<0.05， p<0.1*

From the reverse direction, the population agglomeration pathway shows a significant positive mediating effect (0.233, p<0.01), which means that at the national level, network centrality helps

attract population agglomeration and thus amplifies the advantage of urban economic scale, in line with Hypothesis 6. The local innovation pathway is also significantly positive (0.132, $p<0.01$), indicating that innovation networks can raise local innovation output through knowledge spillovers and further support economic growth, which supports Hypothesis 7. At the national level, innovation networks therefore have a clear role in innovation diffusion and economic promotion, and core cities in the network can more effectively access external knowledge resources and convert innovation outcomes. However, the industrial structure upgrading pathway is not statistically significant, suggesting that the benefits of innovation networks have not yet been stably transmitted into structural transformation effects at the national level.

4.4 Heterogeneity Across City Types

To further examine structural heterogeneity, the model is estimated separately for the four city types (Table 5). Compared with the national level results, which capture average effects, the grouped estimations highlight within type mechanisms and conditional heterogeneity.

The results show that the bidirectional relationship between urban economic scale and innovation networks remains significantly positive across all four city types, with coefficients that are highly similar. This indicates a robust and stable mutual reinforcement relationship between scale and network embeddedness, regardless of development stage. Larger economic scale consistently enhances innovation network embeddedness, while higher network centrality also promotes economic growth, confirming the universal nature of the “scale-network” coupling relationship.

In contrast, the mediating pathways exhibit clear heterogeneity. In the transmission from economic scale to innovation networks, the labor matching pathway remains consistently positive (0.155 to 0.158, $p<0.05$), while the industrial agglomeration pathway remains consistently negative (-0.192 to -0.195, $p<0.01$), consistent with the national results. This confirms that labor mobility is a robust mechanism through which economic scale translates into network embeddedness, whereas excessive industrial agglomeration weakens network openness due to knowledge closure and structural homogeneity. The policy preference pathway, while insignificant at the national level, becomes marginally significant and positive across all city types, suggesting that policy support plays a conditional and auxiliary role whose effectiveness depends on local development conditions.

Table 5 estimation results for different city types from the generalized structural equation model

Pathways	Network driven cities	Resource mismatch cities	Leapfrogging cities	Double lagging cities
Core Bidirectional Relationship				
ln*GDP* → ln*NC*	1.832***	1.895***	1.783***	1.812***
ln*NC* → ln*GDP*	0.141***	0.122***	0.147**	0.121*
Indirect Transmission Pathways (ln*GDP* → ln*NC*)				
Via Industrial Agglomeration (ln*GDP* → ln*indus* → ln*NC*)	-0.193***	-0.192***	-0.195***	-0.192***
Via Labor Matching (ln*GDP* → ln*flow* → ln*NC*)	0.158**	0.158**	0.155**	0.156***
Via Policy Support (ln*GDP* → ln*tech* → ln*NC*)	0.104*	0.104*	0.103*	0.104*
Indirect Transmission Pathways （ln*NC*→ln*GDP*）				
Via Population Agglomeration (ln*NC* → ln*pop* → ln*GDP*)	-3.977***	-6.028***	-5.032***	-8.900***
Via Local Innovation (ln*NC* → ln*innov* → ln*GDP*)	-0.056	-0.048	-0.061	-0.059
Via Upgrading of Industrial Structure (ln*NC* → *upon* → ln*GDP*)	0.030**	0.026**	0.025**	0.026**

Note: *** p<0.01，** p<0.05，p<0.1*

In the reverse direction, the population agglomeration pathway, which is positive at the national level, becomes significantly negative across all city types (-3.977 to -8.900, p<0.01). This indicates strong scale dependence in the population channel. While at the national level innovation centers attract population and resources overall, within homogeneous city groups the strengthening of innovation networks may intensify population concentration toward a limited number of core nodes, leading to population loss in peripheral cities and weakening their economic growth capacity. The local innovation pathway is not significant across all city types, suggesting that within-group

variation does not translate into stable innovation driven economic effects. By contrast, the industrial structure upgrading pathway is significantly positive across all city types (0.025 to 0.03, p<0.05), although it is not significant at the national level. This implies that innovation linkages facilitate integration into higher-value-added value chains and promote structural upgrading, but these effects are offset in the aggregate by heterogeneous effects across different city types.

5 Discussions and Conclusions

5.1 Discussions

This study examines the bidirectional interaction between urban economic scale and innovation networks, highlighting how their co-evolution reshapes spatial inequality and innovation organization within China's urban system. The results contribute to ongoing debates in urban geography on whether urban development is primarily driven by hierarchical scaling processes or by relational network structures, and how these two logics interact in practice.

First, the findings reveal a robust but asymmetric feedback relationship between urban economic scale and innovation networks. Economic scale and network centrality mutually reinforce each other, generating a cumulative causation process that strengthens the hierarchical structure of the urban system. This finding is consistent with cumulative causation theory and previous studies emphasizing self-reinforcing growth dynamics in urban systems (Bettencourt et al., 2007). It also supports recent evidence suggesting that interactions between urban hierarchies and flow networks can amplify intercity inequalities (Zhou et al., 2026a). However, the asymmetric relationship suggests that network formation is not an autonomous relational process but is still strongly embedded in pre-existing economic hierarchies. In the context of China's development trajectory, this asymmetry may reflect the continued dominance of scale-based accumulation logics over relational coordination mechanisms, limiting the capacity of weaker cities to leverage network integration into structural upgrading.

Second, the mediating pathways through which urban economic scale influences innovation networks exhibit substantial heterogeneity. The positive effect of the labor matching pathway indicates that cross city population mobility and the resulting knowledge spillovers and talent matching constitute a core channel through which economic scale is translated into innovation network advantages. This provides a micro level explanation for the sources of innovation vitality in large Chinese cities. By contrast, the negative effect of industrial agglomeration modifies the

conventional expectation that spatial concentration always promotes innovation. Traditional agglomeration theories generally argue that industrial concentration improves productivity and innovation through localization externalities and knowledge spillovers (Krugman, 1991). However, more recent studies increasingly suggest that excessive concentration may generate structural rigidity, path dependence, and network closure (Barboza and Braga, 2025; Boschma, 2005). The present results provide empirical support for this argument by showing that highly concentrated industrial systems may strengthen localized interactions while weakening broader intercity collaboration.

Third, the role of innovation networks in shaping economic scale is highly dependent on scale and context. While innovation network centrality is positively associated with population concentration at the national level, the within-type analysis reveals an opposite effect, where stronger network embeddedness is associated with population loss in peripheral cities. This divergence highlights a scale-dependent reversal mechanism: at the system level, innovation networks reinforce urban concentration by attracting population toward core nodes, whereas within comparable city groups, network intensification may exacerbate internal redistribution pressures and amplify outflows from less competitive cities. This finding suggests that innovation networks operate not only as integrative structures but also as selective mechanisms that intensify uneven spatial development.

Overall, these findings position urban economic scale and innovation networks not as independent growth drivers, but as mutually constitutive forces embedded in a hierarchically structured and unevenly integrated urban system. The interaction between them reinforces existing spatial inequalities while simultaneously generating differentiated local trajectories depending on cities' stage of development.

5.2 Conclusions

By constructing a generalized structural equation model, this study analyzes the interaction mechanisms and transmission pathways urban economic scale and innovation networks. The main conclusions are as follows.

First, there is a stable superlinear relationship between urban economic scale and innovation network centrality, although the strength of this relationship shows a declining trend over time. In terms of spatial distribution, network driven cities are highly concentrated in the three major urban agglomerations, while double lagging cities are widely distributed in western and northeastern China.

Most city types remain stable over time, indicating strong path dependence in the co-evolution of economic scale and innovation networks.

Second, urban economic scale and innovation network centrality reinforce each other and form a positive feedback loop between scale and network. The effect of economic scale on innovation networks is stronger than the reverse effect, and this asymmetric bidirectional relationship is highly consistent across different city types, indicating the fundamental role of economic scale in shaping innovation network structure.

Third, the indirect transmission mechanisms from urban scale to innovation networks exhibit clear divergence. The labor matching pathway plays a consistently positive enabling role, suggesting that population mobility is a key bridge linking scale and network. The industrial agglomeration pathway exhibits a negative locking effect, indicating that excessive specialization may lead to knowledge homogeneity and reduced network openness. The policy preference pathway is ineffective at the national level, suggesting limited capacity of top-down policy allocation to improve network position due to low conversion efficiency.

Fourth, the mediating effects of innovation networks on urban economic scale show differentiated mechanisms. The local innovation pathway is not significant, indicating that increases in patent output driven by network linkages are insufficient to generate sustained economic growth. The population agglomeration pathway exhibits opposite effects at the national and grouped levels, revealing the coexistence of attraction and displacement effects of innovation hubs. The industrial structure upgrading pathway is consistently positive across all city types, confirming that innovation networks promote economic expansion by facilitating movement toward higher value-added industrial structures.

5.3 Policy Implications

Drawing on the empirical findings, several policy implications are proposed to optimize China's urban innovation network structure and promote coordinated regional development.

First, it is necessary to mitigate the polarization effect of the “scale-network” positive feedback loop through differentiated regional strategies. For network driven cities, innovation resources should be moderately decentralized to avoid diminishing marginal returns caused by excessive agglomeration. For leapfrogging cities, policy efforts should focus on strengthening the transformation of network advantages into economic scale, enabling innovation linkages to translate

into local growth. For resource mismatch cities, structural contradictions between large economic scale and weak network embeddedness should be addressed by improving the alignment between traditional industries and innovation networks. For double lagging cities, targeted support policies are required, as market mechanisms alone are insufficient to close the gap with leading cities.

Second, labor mobility channels should be improved to prevent excessive industrial agglomeration. Administrative barriers to talent mobility should be reduced, and mechanisms such as short-term dispatching, project-based collaboration, and remote cooperation should be encouraged to facilitate the diffusion of high skilled labor toward lagging cities. At the same time, urban talent cultivation systems should be strengthened to improve labor matching efficiency. Industrial relocation from core cities should also be guided in a gradual manner to avoid locking in effects, while peripheral cities should be supported in undertaking transferred industries and developing specialized industrial clusters.

Third, science and technology policy orientation should shift from localized investment toward cross regional collaboration. Policy resources should be allocated more toward intercity innovation platforms and collaborative networks rather than localized input, so as to reduce inefficiencies associated with duplicated investment. Joint industry university research alliances should be promoted across cities, along with shared access to research facilities, key laboratories, and data resources.

Finally, greater attention should be paid to the coordinated interaction between industrial upgrading and human capital. Innovation outcomes should be more effectively translated into industrial transformation rather than remaining at the level of output expansion. At the same time, the dual effects of population agglomeration should be addressed by optimizing both the quality and structure of human capital. Enhancing labor mobility can help break rigid industrial network structures and foster a virtuous cycle among innovation, population dynamics, and economic growth.

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Figures legends

Figure 1. Spatial distribution of China's innovation network based on patent cooperation (2018, 2023)

Figure 2. Theoretical analysis framework

Figure 3. Structural equation model of the interaction between urban hierarchy and innovation networks

Figure 4. Power-law relationship between urban innovation network centrality and economic scale

Figure 5. Spatial distribution pattern of different city types (2018, 2023)

Figure 6. Estimated results of the structural equation model

Data availability

The authors declare that the data supporting the findings of this study are available within the paper and its Supplementary Information files. Should any raw data files be needed in another format they are available from the corresponding author upon reasonable request.

Competing interests

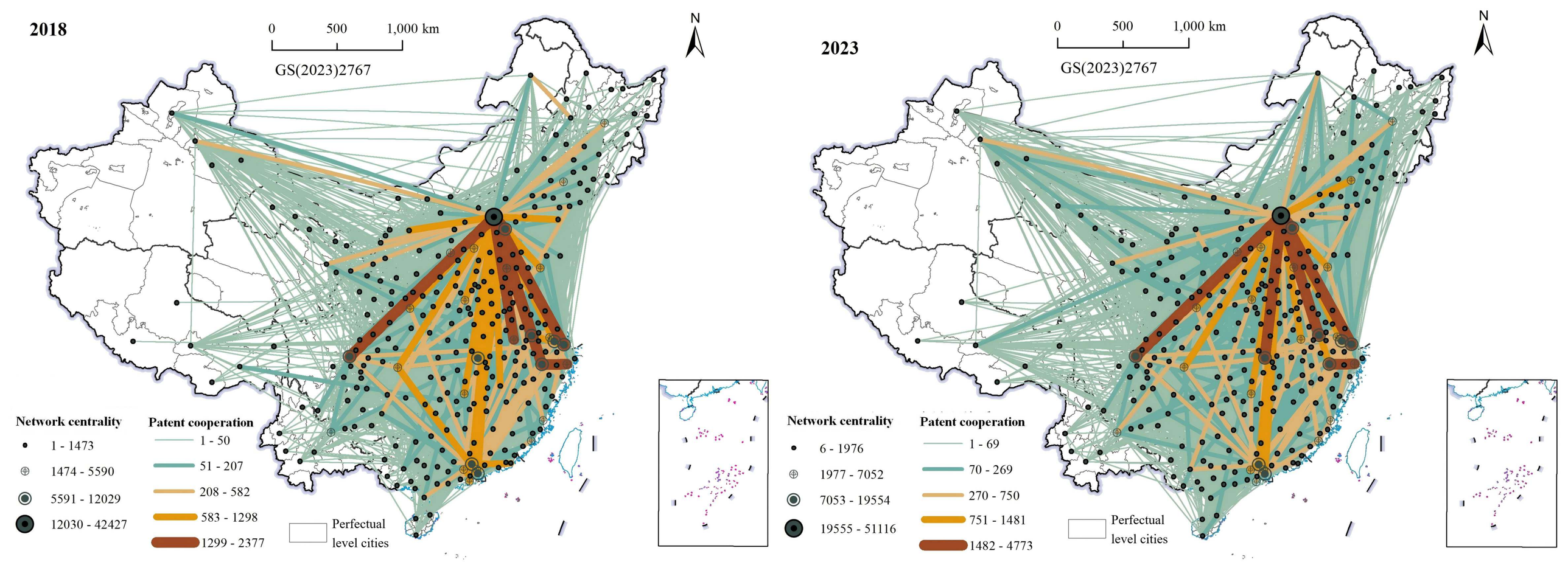
The authors declare no competing interests.

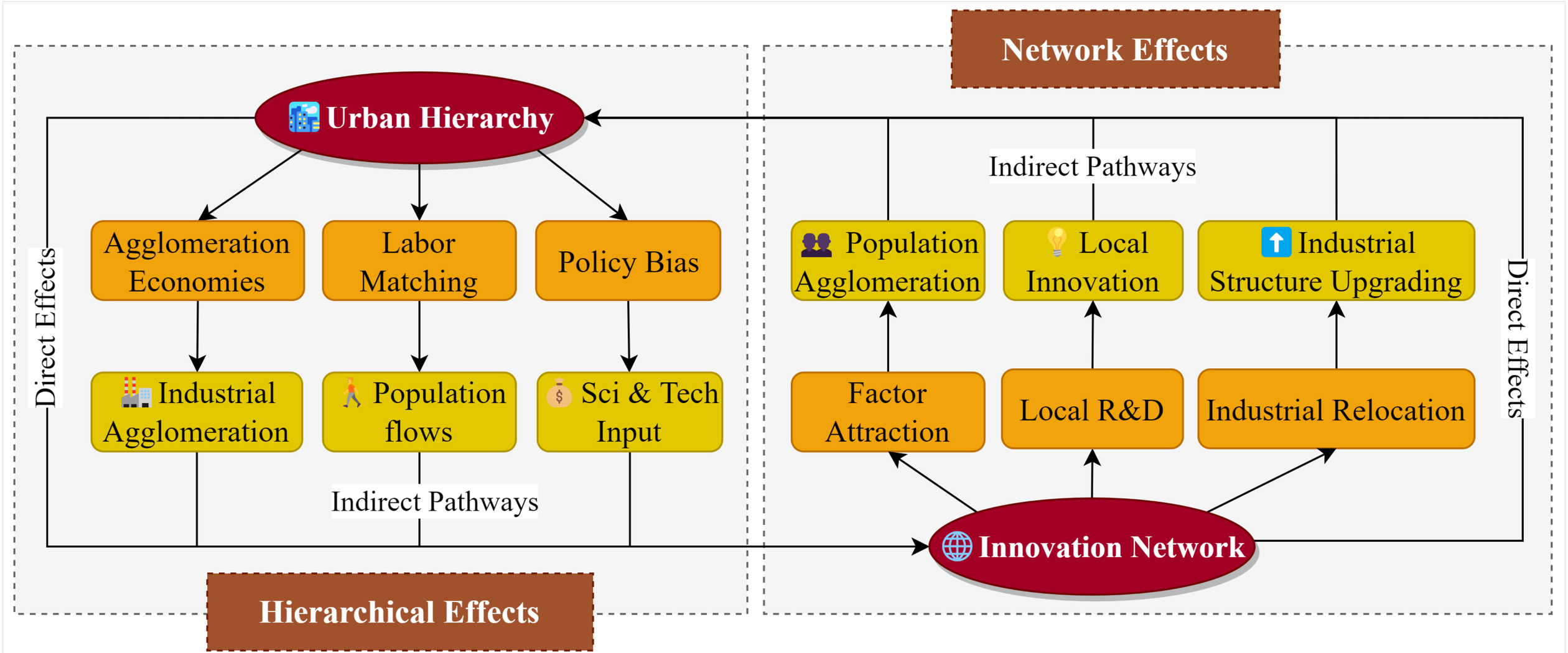
Ethical statements

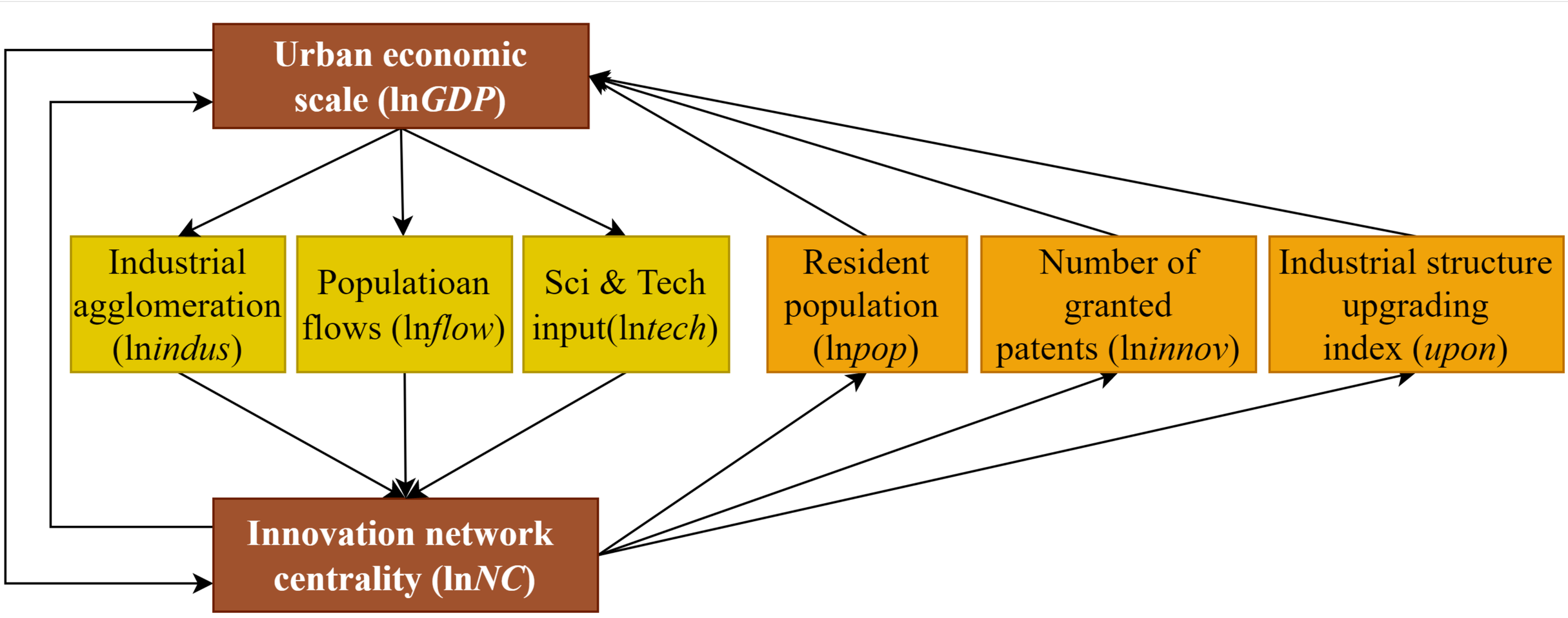
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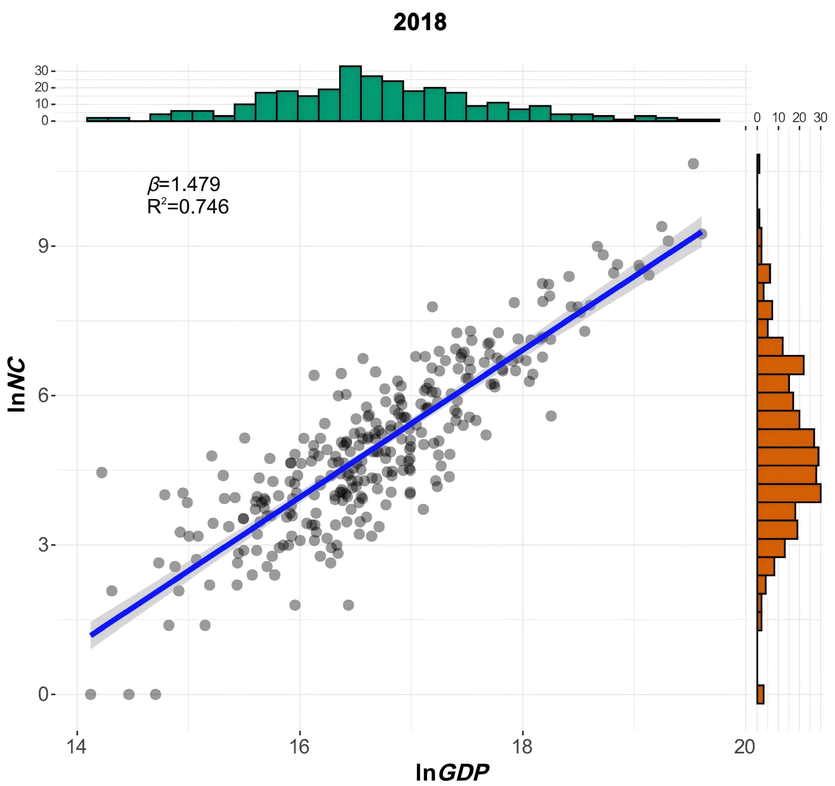
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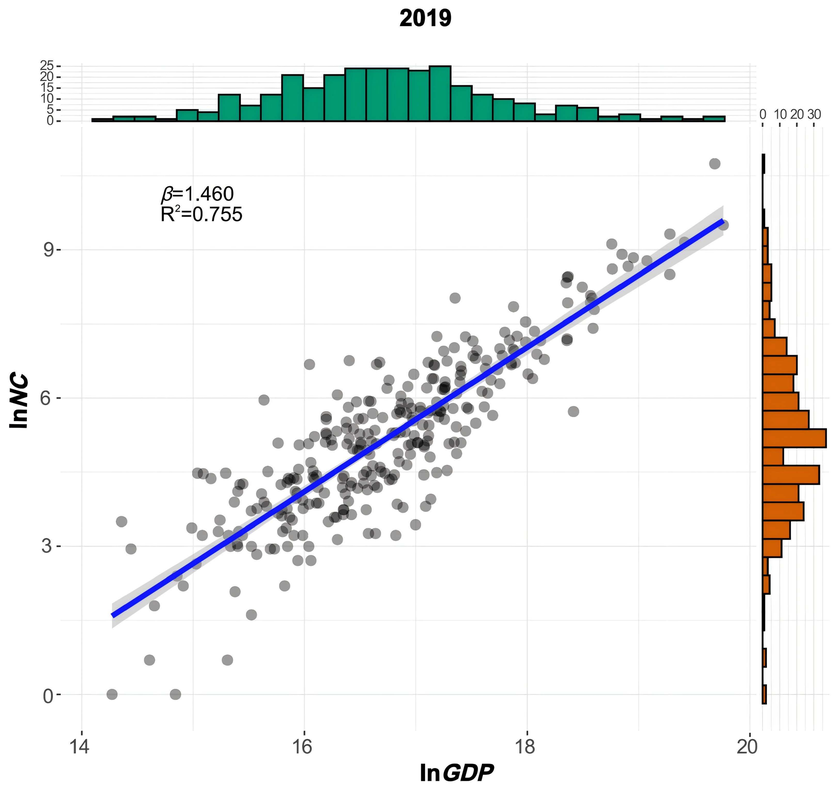
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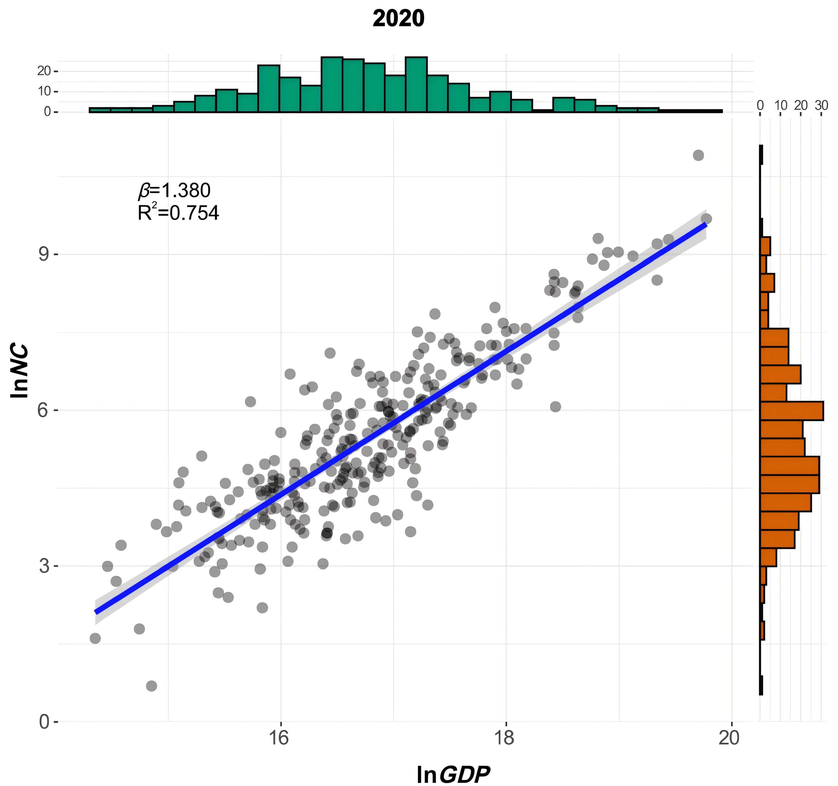

2018
0
500
1,000 km
GS(2023)2767
N
Network centrality
1 - 1473
1474 - 5590
5591 - 12029
12030 - 42427
Patent cooperation
1 - 50
51 - 207
208 - 582
583 - 1298
1299 - 2377
Perfectual level cities
2023
0
500
1,000 km
GS(2023)2767
N
Network centrality
6 - 1976
1977 - 7052
7053 - 19554
19555 - 51116
Patent cooperation
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70 - 269
270 - 750
751 - 1481
1482 - 4773
Perfectual level cities

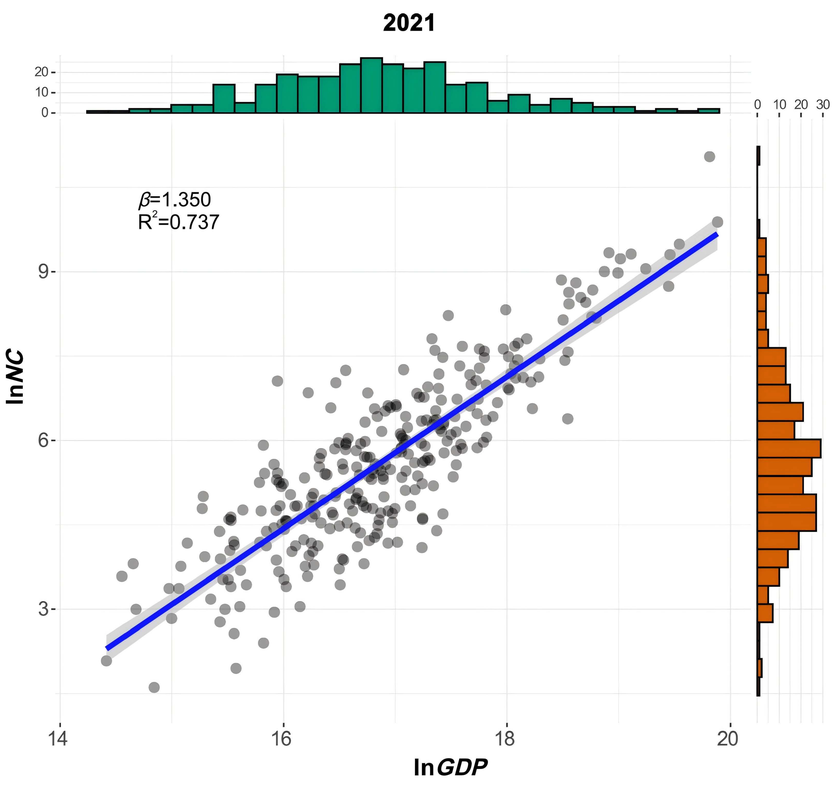

Network Effects
Urban Hierarchy
Agglomeration Economies
Labor Matching
Policy Bias
Industrial Agglomeration
Population flows
Sci & Tech Input
Direct Effects
Indirect Pathways
Population Agglomeration
Local Innovation
Industrial Structure Upgrading
Factor Attraction
Local R&D
Industrial Relocation
Innovation Network
Direct Effects
Indirect Pathways
Hierarchical Effects

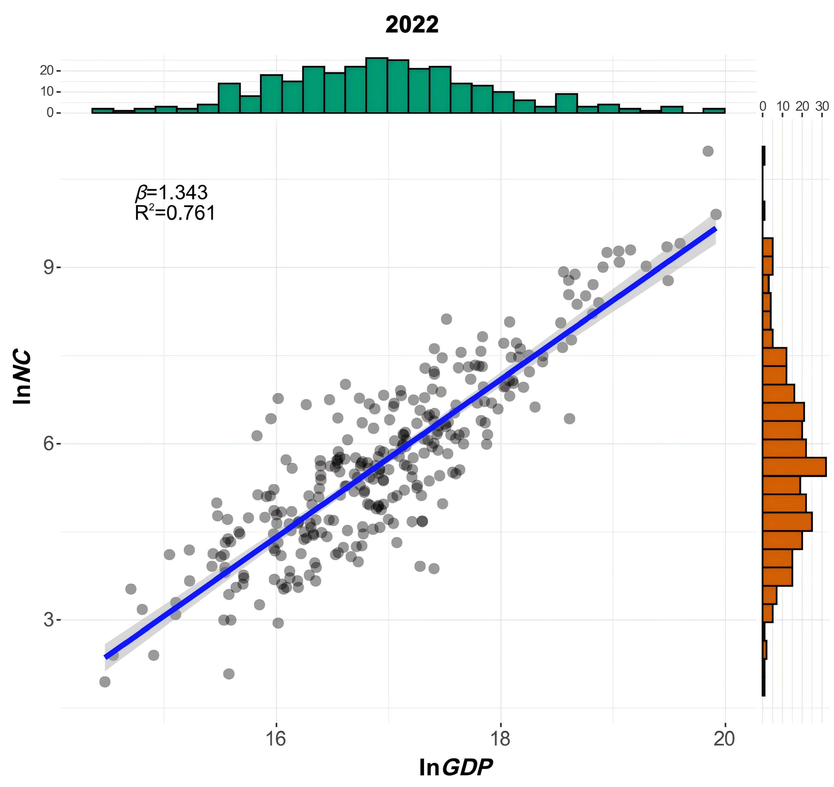

Urban economic scale (ln*GDP*)
Industrial agglomeration (ln*indus*)
Populatioan flows (ln*flow*)
Sci & Tech input(ln*tech*)
Resident population (ln*pop*)
Number of granted patents (ln*innov*)
Industrial structure upgrading index (*upon*)
Innovation network centrality (ln*NC*)

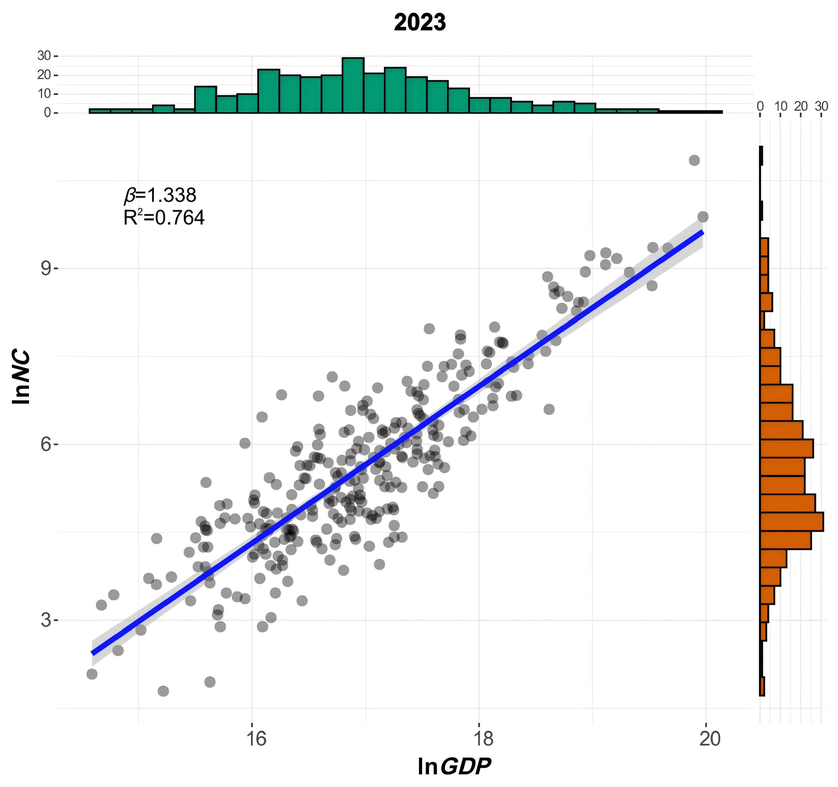

2018
β=1.479
R²=0.746
lnNC
lnGDP

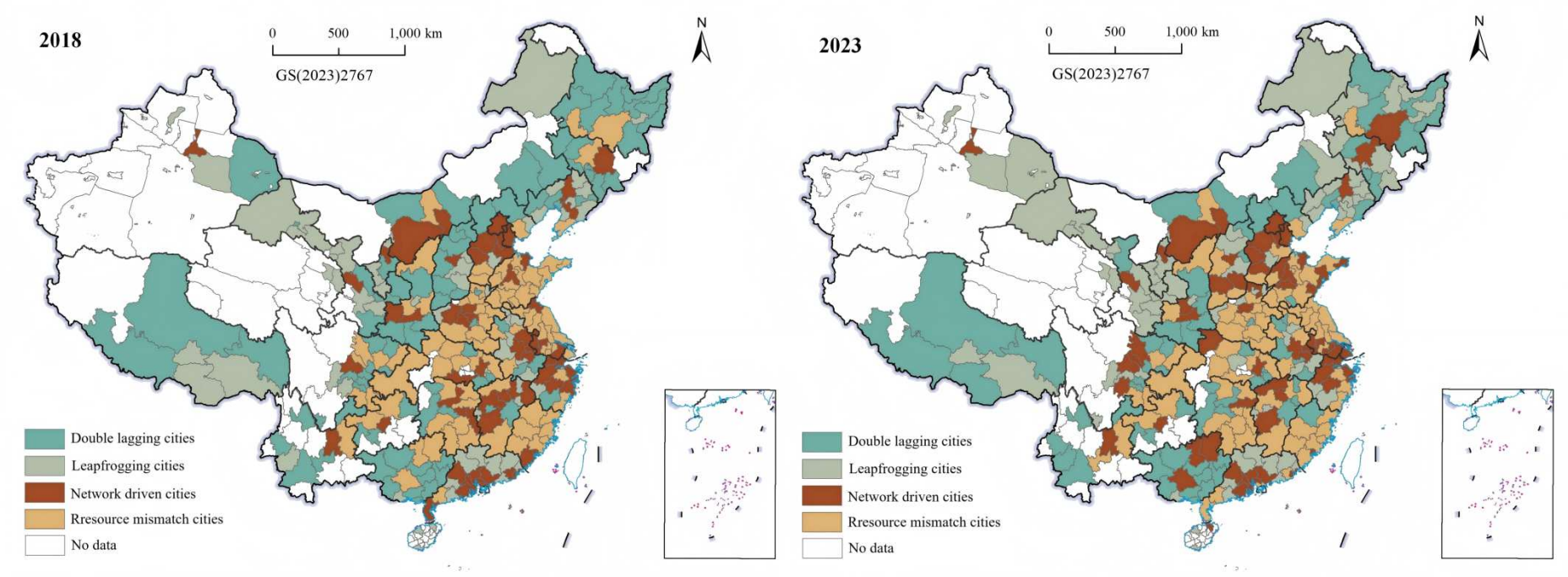

2019
β=1.460
R²=0.755
lnNC
lnGDP

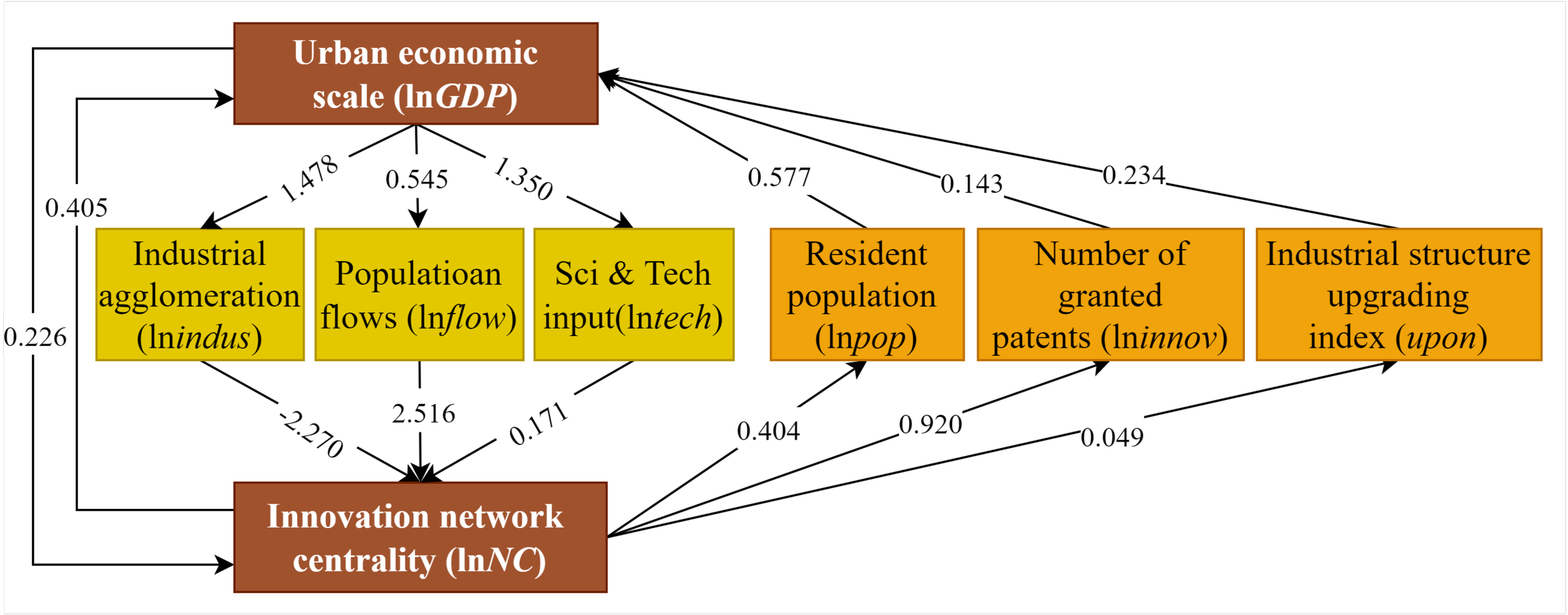

2020
β=1.380
R²=0.754
lnNC
lnGDP


2021
β=1.350
R²=0.737
lnNC
lnGDP


2022
β=1.343
R²=0.761
lnNC
lnGDP


2023
β=1.338
R²=0.764
lnNC
lnGDP


2018
0 500 1,000 km
GS(2023)2767
N
Double lagging cities
Leapfrogging cities
Network driven cities
Rresource mismatch cities
No data
2023
0 500 1,000 km
GS(2023)2767
N
Double lagging cities
Leapfrogging cities
Network driven cities
Rresource mismatch cities
No data


Urban economic scale (ln*GDP*)
Industrial agglomeration (ln*indus*)
Populatioan flows (ln*flow*)
Sci & Tech input(ln*tech*)
Resident population (ln*pop*)
Number of granted patents (ln*innov*)
Industrial structure upgrading index (*upon*)
Innovation network centrality (ln*NC*)
1.478
0.545
1.350
0.577
0.143
0.234
0.405
0.226
-2.270
2.516
0.171
0.404
0.920
0.049

Supplementary Files

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- dataanddo.zip